Ground-Based Scatterometer Measurements and Inversion of Surface Parameters by Using Neural Networks

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***Abstract*-In this study, a multi-band FM-CW ground-based scatterometer is used to measure the backscattering coefficient of bare soil surface. Combined with the neural network (NN) and the advanced integrated equation model (AIEM), it inverses all the soil parameters, including dielectric constant, root mean square (RMS) height and correlation length. According to different data sources, the NN can be constituted as different input-output mapping mode. The NN is trained by using theoretical data that are simulated by the AIEM. The measured data are an input to the NN to inverse the soil parameters. The inversion results have a better consistency with the sampling parameters of soil. More redundancy scattering data can improve accuracy and stability of the inversion. In addition, the scattering measurement experiment is an effective mean of studying scattering model and the inversion algorithm of microwave remote sensing.**

***Keywords*- Scatterometer; Neural Network; AIEM; Roughness; Dielectric Constant; Soil Moisture**

I. INTRODUCTION

The study of microwave scattering models and inversion algorithms can contribute to a better information extraction from microwave remote sensing (RS) data, such as classification, identification, and interpretation of SAR image. In recent years, significant progress has been made in the ability to acquire remotely sensed data with the addition of new airborne and spaceborne sensors. But it is still difficult to retrieve soil moisture and geometry parameters from this data [1]. The backscattering coefficient is decided not only by the soil moisture content, but also by the surface roughness and the presence of vegetation. It is difficult to isolate the contributions from each of these sources. The relationship between soil moisture and the received backscattering coefficient is nonlinear and the problem of retrieving parameters may be ill-posed.

Many efforts have been made to overcome these difficulties. On one hand, there are several microwave scattering models that have been developed from randomly rough surfaces, including Geometric Optics Model (GOM), Physics Optics Model (POM) and Small Perturbation Model (SPM) [2] [3]. Effort has been made to broaden the range of validity over the small perturbation model (SPM) and the classical Kirchhoff. Then a surface scattering model derived from the integral equation method (IEM) [4] has bridged the gap between these two models successfully. After that the IEM is improved for the advance IEM (AIEM) [5]. AIEM has demonstrated that the standard Kirchhoff and small perturbation models (SPM) are special IEM cases in both high and low-frequency regions. It has been widely used to interpret measurement data from laboratory-controlled experiment and field measurements. On the other hand, the development of empirical or semi-empirical models has been used to extract soil moisture. The experience models which can be used on inversion of dielectric constant and roughness include Oh model [6], Dubois model [7] and Shi model [8]. These empirical models ranged among radar backscatter and spatial and temporal variations of soil moisture have been developed and successfully applied to several specific data sets. However, they are generally valid only for conditions under which those measured data were taken. And because that some of the models ignore one of the surface parameters, so these empirical models have limited range of applicability. In addition, soil parameters are retrieved from the radar scattering coefficients by using the theoretic-based optimizing [9]. By optimizing soil parameters, the object function reaches the minimum value. The object function is defined as the RMS of difference between the calculated backscattering coefficient and the radar data. Because the local minimum point and the ill-posed function, this is a time-wasting method. Its accuracy is not acceptable [10]. Neural network (NN) [11] regression is the most proper method to overcome these difficulties. After training the network by the patterns generated by theoretical model, this method can estimate soil parameters rapidly and accurately [1].

However, there is a problem. The model and inversion algorithms often lack of support of measurement data, which include backscattering coefficient and the surface parameters, and also must be obtained synchronously. So it is difficult to verify and improve the model effectively. And the range of applicability is also limited. In this paper, a frequency modulated continuous wave (FM-CW) and ground-based scatterometer are used to measure the backscattering coefficient of bare soil. The measurement data include multi-band, multi-angle and full-polarization backscattering coefficient, while the surface parameters include soil moisture, RMS height and correlation length. The training patterns used to train this network are developed by using the AIEM model. In this way we can choose different training patterns according to the practice radar measurements, and also control the content and ranges of the surface parameters. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, which can be used to inverse the surface parameters directly. Finally, the scatterometer data are an input to the trained NN to inverse the soil parameters, including soil moisture, RMS height and correlation length. The NN achieves two different training patterns of soil parameters inversion. A comparison of the

actual measurement data and the inversion results shows that the NN inversion method has a high accuracy. This approach gives one more option which may be useful for the inversion of soil moisture and surface roughness statistics.

II. GROUND-BASED SCATTEROMETER MEASURING SYSTEM AND MEASURING DATA

A. Scatterometer Measurement System

The ground-based radar scatterometer (GBRS) was constructed by University of Electronic Science and Technology of China (UESTC) [12]. The sensor is carried by the radar of FM-CW. The dual-antenna system maintains the monostatic radar performance, which can measure the backscattering coefficient among -45 and 20dB, with target distance from 10 to 100 m. The microwave scattering measurement system is configured with four different pairs of parabolic antennas, and each of the antenna has a transmitting channel illuminating the soil with a linearly (h or v) polarized electromagnetic wave and a receiving channel detecting the linearly polarized (h or v) wave backscattered from the target. The system can measure full-polarizations. The GBRS system has a tilt and azimuth scanning capability of the ground-based radar platform; it can transform the incidence angle or pitch angle range from 0° to 90°, azimuth angle range from 0° to 360°. The system is equipped with four operating frequency which are L-band (center frequency of 2 GHz), S-band (center frequency of 3.1 GHz), C-band (center frequency of 5.3 GHz), X-band (center frequency of 10 GHz).

Figure 1. The picture of bare soil measurement site

The computer and scatterometer are connected with a standard serial interface RS232 communication cable, whose communication distance can reach 15m. The bare soil measurement is shown in Figure 1. The computer software can achieve continuous and automatic measurements in different incidence angles. All measured data are automatically saved in the database. The measuring procedure is described as follows.

1) Install support structure of the scatterometer, and connect the cable to the system for power.

2) Input the measurement mode (including continuous, single, step scan, angle range) from the host computer interface to the numerical control equipment by the host computer in order to control the turntable of antennas, transmitters, receivers, calibration switches,.

3) The scatterometer measures the distance between antenna and target by using spectral analysis techniques. Then it uploads target echo energy, the current angle of incidence, and all other information.

4) All information is displayed in the host computer interface, and stored on the hard drive of host computer.

First, internal calibration of the scatterometer is carried. A 27-m coaxial line is used as a delay line, and a step attenuator is used as attenuation for the internal calibration procedure. According to the radar equation and internal calibration procedures [2], the backscattering coefficients in the work state were calculated as the following expression:

$$\sigma_0 = \frac{P_m}{P_{im}} \cdot \frac{L_{im}}{L_m} \cdot \frac{P_{ic}}{P_c} \cdot \frac{L_c}{L_{ic}} \cdot \frac{\sigma_c}{R_c^4} \cdot \frac{4R_m^2 \cos\theta}{\pi\beta_V \beta_H} \tag{1}$$

where σ_0 is the backscattering coefficient, R is the distance of the antenna to the observed target, P is the attenuation of receiver channel controllable attenuator, and L is the output power of scatterometer. Subscript *m*, *c*, and *i* are measurement status, external calibration status, and calibration status, respectively; β_V is vertical plane beam width of antenna, and β_H is horizontal plane beam width, θ is incidence angle.

To complete external calibration polarimetric scatterometer, the experiment obtains full polarimetric data from known targets whose scattering matrices have independent eigenvectors. The experiments are designed in the field test site to achieve accurate external polarimetric calibration. First, we hang two metal spheres (diameters with 469mm and 580mm) in the air by using hydraulic lifting device to ensure no other objects within five meters radius of each ball. The metal spheres are hung by very small non-metallic wire, whose scattered signal can be ignored. Antenna beam covers the metal sphere, measures it, and scan multiple incidence angles within a certain range. The maximum value is the scattering coefficient of each metal sphere. Second, the calibration of the scatterometer is examined by measuring scattering matrices of different sizes metal spheres at each band [13]. Then the calibrated elements of the scattering matrix are compared with the sphere theoretical values. Finally, in order to verify the accuracy of the calibration, the large metal sphere is used for calibration target, and the small metal sphere is employed as test target. The result shows that the measured values of the co-polarized are within 1 dB of the theoretical results, and the measured effective polarization isolation for the smaller metal sphere is less than-30 dB at each band.

To acquire several independent samples, the scatterometer is mounted on a pivoting platform. At least 36 independent samples are averaged in each measurement, to ensure a 90% confidence interval of 1 dB. The number of independent samples contained in a footprint is the number of resolution cells that fall within the illuminated area. It is computed from the following expression:

$$N_s \approx 2h\beta B_r \tan\theta / \left(c\cos\theta\right) \tag{2}$$

where, N_s is the number of independent samples, h is height from antenna to ground, β is beam width, B_r is modulation band of the scatterometer, there are different β and B_r for different bands, and θ is the antenna incidence. For example,

at 12.5-m height and 45° incidence angle, the C-band scatterometer footprint contains about 11.2 resolution cells. The required independent samples are achieved by acquiring 20 nonoverlapping footprints and pivoting the antenna around a vertical axis. In this case the total number of independent sampling is more than 220 resolution cells. Therefore, the number of independent is from 60 (at incidence angle of 20°) to 5000 (at incidence angle of 80°) at C-band. The other bands are similar to this. After completing the internal and external calibration and statistical average of independent samples, the overall measurement error of the system is less than ±1 dB.

B. Measurement Data

1) The Backscattering Coefficient

In order to get the backscattering coefficient of soil, we carried out a large number of field measurements experiments in October, 2009. The test site was located at an experimental of UESTC field (103º32’24”E, 30º24’11”N) Qionglai County, Chengdu, Sichuan province, China, and the object was the bare soil without sowing of wheat. The data of scatterometer measurement included L, S, C, X band, HH, HV, VH, VV polarization, and the incident angle from 0° to 90° step 1°.

Figure 2 shows the measured polarimetric backscattering coefficient of L/S/C/X-band curve as a function of the incident angle. In theory, microwave backscatter at cross-polarizations, i.e., HV and VH, is equivalent for the same target. Indeed, the overall correlation between the HV and VH coefficients is high along the one-to-one line for all frequencies and incident angles. Therefore, data from both cross-polarizations are averaged for each set of measurements.

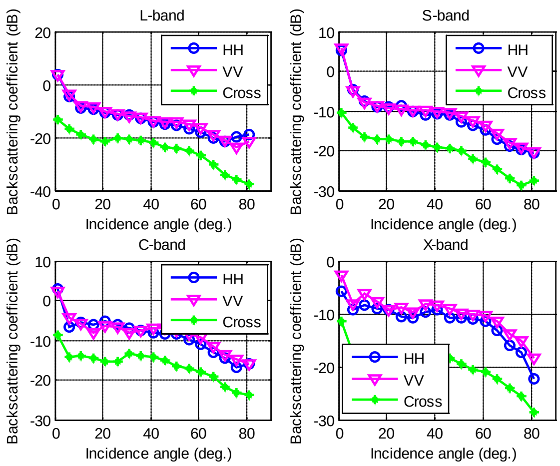

Figure 2. Multi-band scatterometer with different polarization measurements

We can see from the Figure 2 that backscattering coefficient is decreasing as the angle is increasing significantly from 0° to 10° and also from 60° to 80°. A smooth in backscatter is observed from 10° to 60°, and the higher the frequency is, the smaller the change will be. For instance, L band decreases 10 dB, but X band decreases only 2dB from 10° to 60°. There is a certain degree undulation for the bands that have higher frequency including C and X band, which is because that, when the wavelength is shorter, the roughness will have a greater impact on the backscatter coefficient. The backscattering coefficient at VV polarization is higher than that at other polarizations for each band, and is consistent with the simulation results of integral equation method (IEM) [4]. The value of the difference VV and HH polarizations is less than 2dB. The cross-polarization backscatter is similar to the co-polarization that versus incidence angles, but the backscatter value is smaller, at about 6dB (L-band), 8dB (S-band), 9dB (C-band) and 12dB (X-band).

2) The Soil Parameters

Figure 3 (a) (b) and (c) shows the measurement picture of soil parameters, which include roughness, soil sample, soil moisture and dielectric constant. Soil moisture content is measured by using the gravimetric method [2]. The resulting gravimetric moisture content was transformed into volumetric moisture content through multiplication by the soil bulk density. In the experimental area, the moisture is 12.3 % to an average of more than 20 soil samples. The type of soil is clay, which accounts about 50%. Sand takes up 15%. The other types are 35%. The transmission/reflection method is used to measure the soil dielectric constant that based on vector network analyzer [13]. The soil dielectric constant is 5 in using this method. Soil roughness profile is measured at the same time. A 1-m-long needle profiler, with a horizontal resolution of 0.9 cm and an accuracy of about 0.2 cm in the vertical direction [14], is used to measure soil roughness along directions parallel and perpendicular. The average profile RMS height is 1.56 cm, and the correlation length is 15.5 cm. The correlation function is exponentially distributed.

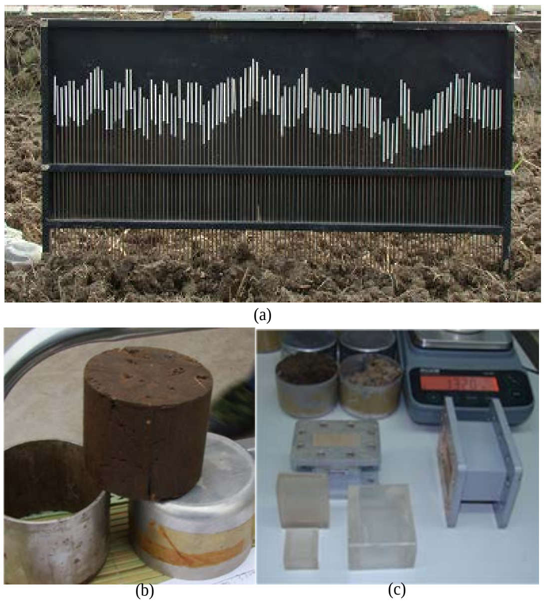

Figure 3. Measurement of soil parameters: (a) soil roughness; (b) soil sample; (c) soil moisture and dielectric constant

III. SOIL MODEL AND NEURAL NETWORK TRAINING

A. BP Neural Network Optimization

Back Propagation (BP) network was applied to the widespread and important neural network. NN theory has proved that BP has a strong non-linear mapping and generalization ability. In the Matlab software, when using NN training to improve the training efficiency and accuracy, we need to notice the following aspects.

1) A Regulation of Training Data

Sample data value (P) and target (T) carried out pre-normalized contribution to the stability of BP network training. In order to avoid over-concentration of data, and improve

speed of training, the data were regulated at the range of [0, 1] in this article.

2) *To Determine the Network Structure*

NN theory theorem Kolmogorov has proved that the three-BP network can approximate any function by full study. However, the experiment showed that the increase of the network layers can improve the training accuracy, so this article used 4 or 5-layer structure of the network for different situations. The three parameters of inversion determined three output nodes. The input layer nodes were the best to set 20 after repeated training. Hidden nodes were determined by the following experience formula:

$$s=\left(0.43mn+0.12n^2+2.54m+0.77n+0.35\right)^{0.5}+0.51 \quad (3)$$

where: s is the hidden nodes, m is the input layer nodes, and n is the output layer nodes. In this paper, we use the network structure of 4 layers (20, s+2, s, 3), or 5 layers (20, s+2, s, s-2, 3).

3) *Choice Learning Algorithm*

Basic BP algorithm makes the MSE tend to minimize by using gradient descent. However, it has a slow pace of convergence and a local minimum in practice. Matlab7.0 NN toolbox provides a variety of fast learning algorithms. The most representative ones are five algorithms: traingdx, trainrp, trainscg, trainoss and trainlm. Experiments show that there is a different limits error for different learning algorithm, so this article uses trainlm for it has the best training accuracy.

TABLE I. DIFFERENT DATA SET ARE GENERATED ACCORDING TO DIFFERENTREQUIREMENTS TO TRAIN ANN

Data Sources			Training data set $\vec{P}$
Pol.	Fre.	Angle	
Full-	Single-	Single-	$\left(\sigma_{hh},\sigma_{vv},\sigma_{cross},\theta\right)$
Single-	Multi-	Single-	$\left(\sigma_{f_1},\sigma_{f_2},\sigma_{f_3},\cdots,\theta\right)$
Single-	Single-	Single-	$\left(\sigma_{\theta_1},\theta_1,\sigma_{\theta_2},\theta_2\right)$
Dual-	Multi-	Single-	$\left(\sigma_{hhf_1},\sigma_{vvf_1},f_1,\sigma_{hhf_2},\sigma_{vvf_2},f_2,\cdots,\theta\right)$
Dual-	Single-	Multi-	$\left(\sigma_{hh\theta_1},\sigma_{vv\theta_1},\theta_1,\sigma_{hh\theta_2},\sigma_{vv\theta_2},\theta_2,\cdots,f\right)$
Dual-	Multi-	Multi-	$\left(\sigma_{hhf_1\theta_1},\sigma_{vvf_1\theta_1},f_1,\right.$ $\left.\sigma_{hhf_2\theta_1},\sigma_{vvf_2\theta_1},f_2,\theta_1,\cdots\right)$

B. *NN Training Data Using AIEM Simulation*

AIEM can effectively simulate backscattering coefficient in a wide range of surface roughness. The backscattering coefficient of the same polarization is a major single-scattering. So this study use single scattering theory model to generate data, and inverse dielectric constant ε, RMS height s and correlation length l at the same time. The model that connects surface parameters and backscattering coefficient can be expressed as the simple formula:

$$\vec{P}=F_{\mathrm{model}}(\vec{T}) \quad \text{or} \quad \vec{T}=F_{\mathrm{model}}^{-1}(\vec{P}) \qquad (4)$$

Here, T is a vector of output parameters, and $\vec{T}=[\varepsilon,s,l]$, P is a vector of output parameters, according to different data. P can be of many different combinations as shown in TABLE 1:

In TABLE 1, all the training data are simulated by the AIEM scattering model. Before training, the effective range of surface parameters is chosen based on the actual situation including the soil dielectric constant ε, the surface RMS height s and correlation of l. Finally, we use the backscattering coefficient simulated by AIEM to combine into a training data set as the table form.

Next, we choose two ways of training and inversion, including full-polarization mode $\vec{P}=\left(\sigma_{hh},\sigma_{vv},\sigma_{cross},\theta\right)$, and dual-polarization, dual-channel mode $\vec{P}=[\sigma_{hhf_1},\sigma_{vvf_1},\sigma_{hhf_2},\sigma_{vvf_2},\theta]$.

C. *The Results of Training and Error*

1) *Full-polarization Mode*

The training data P is selected HH, VV and cross polarization at S-band (3.1GHz), and the incident angle is from 10° to 70° step 5°. The ranges of output parameters T are set. Dielectric constant ε is from 5mm to 35mm step 3mm. RMS height s is from 8mm to 35mm step 3mm. And correlation length is from 30mm to 170mm step 10mm. Then the full-polarization mode is trained by using these data that are simulated by the AIEM. After completing the training of network, the NN has achieved correspondence from full polarization data to the soil parameters. Figure 4 shows the soil parameter inversion value.

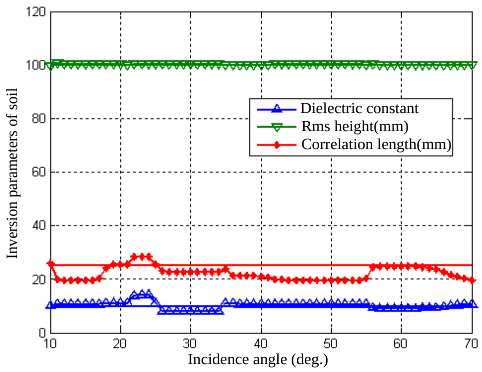

Figure 4 The three soil parameter inversion value obtained from the trained NN

In Figure 4, the three straight lines are input values of the AIEM, and the AIEM output values are the NN input. They get the output value express to three curves with symbols. As it can be seen from Figure 4, the inversion value of NN is very close to the input values of the AIEM. This means that the NN has very good correspondence from full polarization data to the soil parameters. It is shown that the NN can be used to invert three soil parameters by providing full polarization data

2) *Dual- polarization and Dual Frequency Mode*

Two-frequency has been selected as 3.1GHz and 5.3GHz which are scatterometer frequency of S-band and C-band. Polarization is HH and VV. Other parameter set is the same to full-polarization mode. The training data for input data set P and output data set T are generated by the AIEM. Then we use these data to train the BP NN. After completing the training of network, the NN can be used to invert the soil parameters. Training error decline curve in the process and inversion results of different angles have been shown in Figure 5.

We can see the error decline curve quickly but reach a high precision in this training mode from Figure 5-a. Figure 5-b/c/d

shows the results of NN inversion, which includes ε, s and l. The error of inversion is less than 2%, so it is feasible to use NN achieve parameters inversion of high-precision. In addition, the experiment shows that reducing the range of parameters can increase training speed and accuracy. Therefore, the range of surface parameters can be reduced appropriately according to the actual situation.

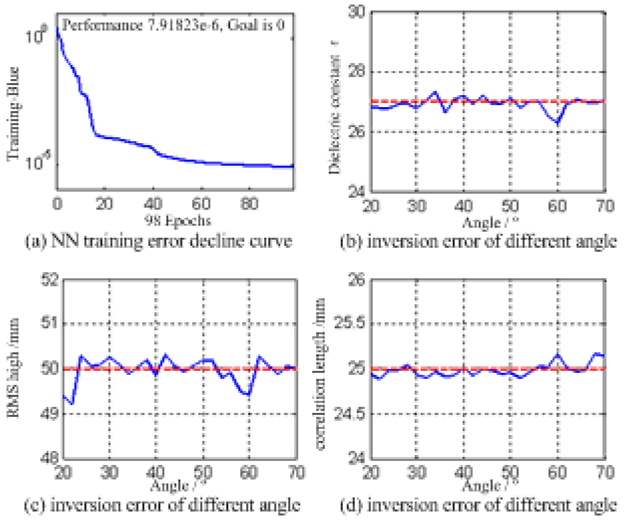

Figure 5 NN training error and inversion testing of different parameters

IV. THE INVERSION RESULTS USING MEASURING DATA OF SCATTEROMETER AND ANALYSIS

A. Full-polarization Mode

The measuring data of HH, VV and cross polarization at S-band are used to add into the input array P: $\bar{P}=(\sigma_{hh},\sigma_{vv},\sigma_{cross},\theta)$. The array input add into the trained NN is to inverse the three soil parameters at different incident angles, and the soil moisture is got from the dielectric constant by using Top empirical formula [15]. Figure 6 shows angular variation of the inversion value. The line represents measured values, and the curve with triangle symbol represents inversion value.

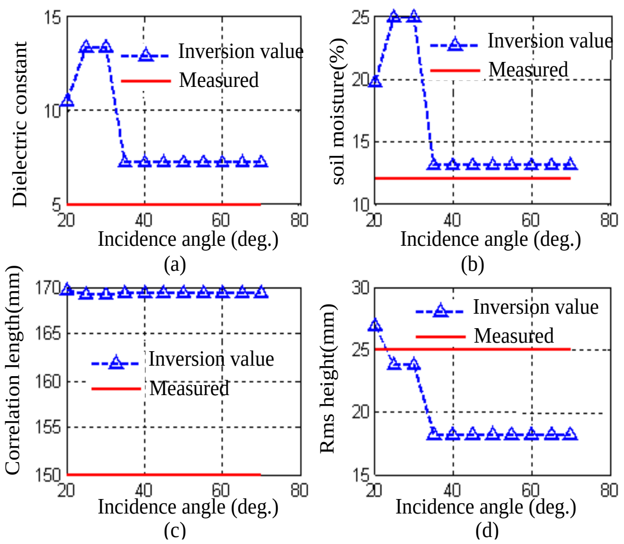

Figure 6 The soil parameters inversion results of different angle use full-polariztion mode: (a) dielectrice constant, (b) soil moisture, (c) correlation length, (d) RMS height.

As can be seen from Figure 4, the inversion value from NN is very close to the measured values. In particular, the error of soil water content and correlation length is less than 15%. The each inversion value is very stable from 35° to 70° which means that the NN provides a greater range of adaptation for incidence angle that covers most of the satellite SAR data. The curves have large fluctuations in small incidence angle (20°-35°) for Figure 6 (a) (b) and (d). Co-polarization difference of AIEM is very little at small incidence angle, so little fluctuations of the measured value will cause large errors.

B. Dual-polarization and Dual-frequency Mode

The measuring data of HH and VV polarization at S-band and C-band are used to combine into the input array P: $\bar{P}=[\sigma_{hhf_s},\sigma_{vvf_s},\sigma_{hhf_c},\sigma_{vvf_c},\theta]$. The array input added into the trained NN is to inverse the three soil parameters at different incident angles, and the soil moisture is also got from the dielectric constant by using Top empirical formula. Figure 7 shows the angular variation of the inversion value. As can be seen from Figure 7, the inversion parameters of dielectric constant and soil moisture are very stable at all incidence angles from 20° to 80°, but the curves of correlation length and RMS height have a certain fluctuations with the incidence angle, particularly at smaller angle (20°-40°). Little fluctuations of the measured value that include co-polarization difference and differences in band will also cause large errors. The error of soil water content of this mode is less than the full-polarization mode. It shows that more extensive data can provide higher accuracy, but may lead to greater instability, such as correlation length and RMS height. In addition, soil surface roughness is uneven at different angles and has different magnifications for inversion error. It is also a factor that leads to fluctuations of curve.

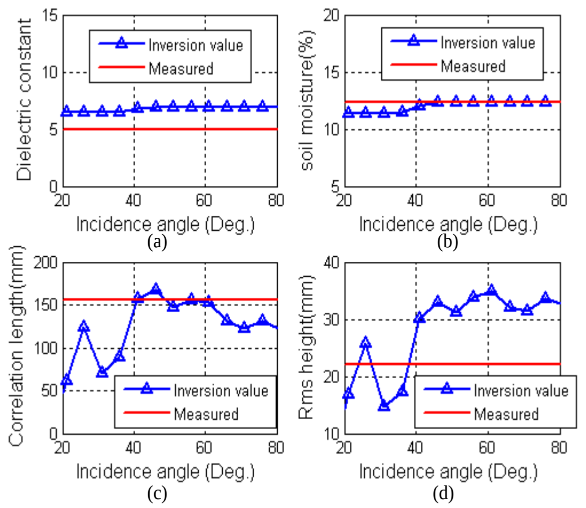

Figure 7 The soil parameters inversion results of different angle use dual-polarization and dual-frequency mode: (a) dielectrice constant, (b) soil moisture, (c) correlation length, (d) RMS HEIGHT height.

Comparing the inversion results with the data, we find that the dielectric constant, RMS height and correlation length are basically the same when the volatility of the curve accords with the fluctuations of the actual measurement data. It shows that the use of scatterometer data for inversing surface parameters is basically viable, and also shows that neural network inverse multi-parameters are effective. Actual measurements found that the roughness of different directions

may be quite different in that, one-dimensional AIEM can not completely reflect the relation between different direction roughnesses with the backscattering coefficient. So we need to study the two-dimensional model and the corresponding roughness characterization.

In addition, the results of the inversion of soil moisture have a lot of difference. The main reason is that, the top formula generally applies to the soil with larger sand content, but not the soil with larger clay content. We use Dobson semi-empirical formula to calculate [16]. When the soil moisture content is 12%, the value of relative dielectric constant is about 7, so it is consistent with the measured data. However, to complete the inversion of the formula Dobson, the imaginary part of dielectric constant value and the dielectric constant relate to the frequency are also needed.

To sum up, inversion accuracy mainly depends on four aspects, including the accuracy of the model simulate surface scattering, the training accuracy of NN, the measurement precision of backscattering coefficient and the measurement accuracy of surface parameters. In general, the inversion accuracy of neural network can be improved through setting the training algorithms and parameters, the measurement accuracy of scatterometer as well, and the direct measurement accuracy of the surface parameters can be ensured easily, so the final inversion accuracy mainly depends on the situation accuracy of model. As a result, it is very important to choose or build a better scattering model that can better simulate the actual surface scattering, especially for the objects that are unknown for the scattering mechanism.

V. CONCLUSIONS

In this paper, NN inversion is realized to all the soil parameters. The theoretical simulation and the experimental data are used to train and verify the BP network. First of all, a multi-band FM-CW ground-based scatterometer is used to measure the backscattering coefficient of bare soil surface. The system parameters of measurement include L/S/C/X-band, full-polarization and different incidence angle. The training data is simulated by using the AIEM model. According to different scattering data, the NN is divided into two different training patterns. The trained NN acts as an empirical mapping relation between the radar measurement and the surface parameters, and it can be used to inverse the surface parameters directly. Finally, by using S-band and C-band measurements data, the trained NN achieve the inversion of three soil parameters. A comparison of the actual measurement data and the inversion results show that the NN inversion method has a high accuracy. There are three following conclusions:

(1) Even though the surface parameters are unknown, it is possible to realize the full inversion of the bare soil moisture and surface roughness parameters by using the multi-polar and multi-band measurements at the same incident angle.

(2) At each training pattern, the trained NN can get an accurate mapping relation between the radar measurement and the surface parameters. So the inversion accuracy depends on the accuracy of the validity of the models upon which the training data are based on the AIEM and dielectric models.

(3) If the input data of NN training patterns want to use the multi-angle data, the soil surface must be very uniform to ensure that the measured of different incidence angle can be used as the same surface. When the same region has multiple SAR data that are from different incident angles, the surface parameters can be inversed by this training pattern.

In short, the NN method has high inversion speed and accuracy. Its inner mapping accuracy is precise enough to be applied in practice. It is an effective means combined with model simulation and ground-based scatterometer experiment to study microwave scattering mechanism. The parameters inversion study using measurement data has some reference value to extract parameters at large-scale of microwave remote sensing. However, the presence of vegetation make the radar return not necessarily attributed from the soil. In this case, the training data must be generated by the vegetation scattering model. Unfortunately, there is no vegetation model that can widely adapt to each planting. And vegetation model has more input parameters, including soil surface and vegetation parameters. To solve this problem, further study will concentrate on the scattering mechanism of crop vegetation by using the ground-based scatterometer and vegetation parameter inversion method of NN.

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